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DETECTING MOTION FROM A MOVING PLATFORM; PHASE 3: UNIFICATION OF CONTROL AND SENSING FOR MORE ADVANCED SITUATIONAL AWARENESS

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14. ABSTRACT
The University of Wyoming has formed a robotics initiative consisting of three distinct parts.
"**Biomimetic Vision Sensor**," (AFRL-RX-TY-TR-2011-0096-01) develops a novel computer vision sensor based upon the biological vision system of the common housefly, *Musca domestica*.
"**Lightweight, Low Power Robust Means of Removing Image Jitter,**" (AFRL-RX-TY-TR-2011-0096-02) develops an optimal platform stabilization mechanism for motion detection and target tracking using recent advances in the area of Parallel Kinematic Machines (PKMs).
"**Unification of Control and Sensing for More Advanced Situational Awareness,**" (AFRL-RX-TY-TR-2011-0096-03) develops a multi-purpose planning scheme that effectively solves patrolling and constrained sensor planning problems for a large-scale multi-agent system.

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1. EXECUTIVE SUMMARY

The University of Wyoming has formed a robotics initiative consisting of three distinct parts. A complete, stand-alone final technical report is presented for each phase. Phase 1 was managed by Dr. Cameron Wright, Phase 2 by Dr. John O'Brien, and Phase 3 by Dr. John McInroy. The overall project was coordinated by the Robotics Initiative Manager, Dr. John McInroy.

Phase 1, "**Biomimetic Vision Sensor**," AFRL-RX-TY-TR-2011-0096-01 summarizes the development of a novel computer vision sensor based upon the biological vision system of the common housefly, *Musca domestica*. Several variations of this sensor were designed, simulated extensively, and hardware prototypes were constructed and tested. Initial results indicate much greater sensitivity to object motion than traditional sensors, and the promise of very high speed extraction of key image features. The main contributions of this research include: (1) characterization of the image information content presented by a biomimetic vision sensor, (2) creation of algorithms to extract pertinent image features such as object edges from the sensor data, (3) fabrication and characterization of sensor prototypes, (4) creation of an automated sensor calibration subsystem, (5) creation of a light adaptation subsystem to permit use of the sensor in both indoor and outdoor real-world environments.

Phase 2, "**Lightweight, Low Power Robust Means of Removing Image Jitter,"** AFRL-RX-TY-TR-2011-0096-02, develops an optimal platform stabilization mechanism for motion detection and target tracking using recent advances in the area of Parallel Kinematic Machines (PKMs). Novel PKM architectures have been developed for high performance disturbance rejection and target tracking. Nonlinear feedback control has been successfully implemented on this hardware allowing for maximum feedback and stability despite the presence of nonlinearities in the feedback loop. Modified command feedforward has been successfully implemented on these PKMs that provides high performance tracking despite significant nonminimum phase delay. The combination of these new PKMs and advanced control methods is a substantial new Air Force capability for future unmanned ground vehicle applications.

Phase 3, "**Unification of Control and Sensing for More Advanced Situational Awareness,"** AFRL-RX-TY-TR-2011-0096-03, develops a multi-purpose planning scheme that effectively solves patrolling and constrained sensor planning problems for a large-scale multi-agent system. This situation arises when some mobile-robots are performing a patrolling mission, and, at the same time, they gather visual data from pre-defined objects in the map. The proposed technique doesn't directly tackle the merged problem with the complicated cost function. Instead, it suggests a sequential scheme that considerably simplifies the main multi-objective problem, and makes it easier to make a compromise. The simulation confirms the effectiveness of the proposed multi-objective multi-agent planning scheme for different size systems.

This report covers Phase 3, "**Unification of Control and Sensing for More Advanced Situational Awareness,"** AFRL-RX-TY-TR-2011-0096-03.

2. INTRODUCTION

Modern robots are equipped with redundant sensors and accurate actuators, and they employ reliable algorithms to continuously update their belief about the location in the environment map (*Localization*[1]*)*. They also exploit powerful path- *planning*[2] techniques to find an adequate path to get to the desired destination. Although localization and path- planning are the most fundamental problems to solve in order to have truly autonomous capabilities, they usually are not the main objective of the robotics. The ultimate goal of an autonomous robot is to effectively accomplish a mission that might be composed of several tasks/sub-tasks [1].

In many applications in robotics, a group of robots should collaboratively perform specific tasks which have dissimilar mathematics representations, i.e. with a different objective function. Since different situations impose distinct constraints on each decision maker, a decent plan of action is required to allocate tasks to agents in this cooperative decision making system. Likewise, a surveillance mission usually consists of different tasks such as patrolling, tracking, object detection, visual data gathering, etc. Many of these tasks are separately studied in literature, while the combinations of those are very occasionally taken into consideration. The main reason is that the combined large-scale problem results in a very complicated formulation, and it demands a meticulous multi-objective planning scheme that achieves diverse goals at the same time. Therefore, making a reasonable compromise to reach a satisfactory result for a large-scale problem would be impractical.

This paper proposes a multi-objective planning scheme that effectively performs *Patrolling* and *constrained visual sensor management* (CVSM) for a large-scale surveillance system. Both patrolling and CVSM are emerging research areas and have various applications in different domains such as surveillance, environmental monitoring, etc. The proposed planning scheme first determines the patrolling trajectories for all agents, and it determines which object should be inspected by which camera at each time step. The ultimate objective is minimizing the maximum time lag between passing by the same place (revisit time) for all desired places. Simultaneously, it is desired to maximize the overall quality of observations. The proposed scheme defines each task's parameters in such a way that they can ensure desirable results. In other words, it reduces the complexity of the original problem by dividing the merged complex problem into sub-tasks at the cost of losing optimality. The proposed multi-objective planning scheme requires a grid-based map, target positions, and patrolling via points as inputs. The algorithm starts with the classic patrolling problem, and solves the corresponding traveling salesperson problem (TSP) to design the best possible trajectories that minimize patrolling time. Then, it partially modifies the trajectories by considering their effects on both task`s performance, and adds one new via point to a trajectory that causes the minimum increase in visiting time. In this process, the patrolling performance gradually degenerates in order to attain an acceptable performance level for the combined scheme. Since the algorithm locally computes the inspection quality of the current patrolling trajectories caused by a specific target, it is computationally fast, and applicable for large-scale multi-agent systems. After the path planning process, a hybrid method is employed to find a near optimal planning for the CVSM problem. Results show that far fewer observations are required to obtain a specific amount of visual information from all sides of the targets.

[1] The process of determining the location of the robot relative to the environment is called *Localization*.
[2] Planning in this context means devising a trajectory from a starting point to a desired destination.

Reference [1] exploits ordered upwind methods to combine area patrol, perimeter surveillance and target tracking problems. Machado et al. (2003) study various architectures of the patrolling problem, and give some guidelines to choose an adequate multi-agent system strategy for multi-agent patrolling tasks. Using a specific class of cyclic strategies, a multi-agent patrolling problem can be modeled as the TSP, and it can be satisfactorily solved in $O(n^3)$ [2]. Xiong and Svensson [3] perform a comprehensive survey about sensor fusion and sensor management methods and its issues. Tarabanis et. al. [4] exclusively investigate visual sensor management in the 3-D computer vision area. In order maximize the quality of information, [5] conclusively establishes entropy based information metrics to differentiate effective sensors.

This report is organized as follows. Section 3 begins with a brief problem description of the Multi-Objective Multi-Agent system followed by its sub-tasks (patrolling and CVSM) in Sections 3.1 and 3.2. Section 3.3 explains the proposed coordinated design procedure. Section 4 contains all simulations for different problem instances. We conclude in Section 5 with recommendations.

3. METHODS, ASSUMPTIONS, AND PROCEDURES

The proposed planning scheme is aimed at solving a class of Multi-Objective Multi-Agent problems that can be represented as a patrolling and CVSM problem. This situation occurs in many surveillance applications whenever a number of agents are patrolling an area, and collect information from some prime targets. The proposed scheme is applicable to any similar applications.

The theory will be developed within the context of ground situational awareness. In order to keep the report self-contained as much as possible, in the subsections 3.1 and 3.2, we briefly review both constituent problems, and explain all requisite theoretical aspects. Afterwards, Section 3.3 elaborates the formulation of the mixed problem.

3.1. Patrolling

Patrolling is the act of repeatedly traversing a region in order to perform condition monitoring and detect unexpected changes in the map states. There are two different approaches to perform patrolling: *deterministic* and *probabilistic*. Probabilistic methods are designed to prevent adversaries from entering a specific area by minimizing the penetration probability. They employ randomized strategies to make the routes unpredictable.

Deterministic approaches achieve less sweeping time for a group of agents and visit all key points in a fixed area. Our new method is specifically designed for the latter patrolling strategy. However, since the overlapping trajectories are complex and unknown to an adversary, they still maintain low penetration probability in most cases. Because new trajectories can automatically be generated very quickly without human intervention, they can be changed often to keep the patrols from becoming predictable.

It can be shown that the deterministic patrolling problem can be formulated as a TSP which can be effectively solved by an approximate method [6].

3.2. Constrained Visual Sensor Management

VSM's main objective is to specify the parameters of the vision system to obtain worthwhile information from the environment [7]. The CVSM problem is a special case of VSM in which the agents (cameras) and targets are subject to some constraints, e.g. they are moving on specific paths. A CVSM problem size is relatively smaller in terms of the number of unknown variables than VSM. Consequently, it is easier to find an optimal solution for a small size CVSM problem. However, a large-scale CVSM problem is much harder to solve due to a lot of linear/non-linear constraints. It can be shown the CVSM can be formulated as an Integer Linear Programming (ILP) problem [8] which lies in the strongly NP-hard class of combinatorial optimization problems. Like the TSP problem, no *Polynomial Time Approximation Scheme* (PTAS) has been discovered to find an optimal solution for such problems.

Suppose decisions are represented by $U \in \mathbb{B}^{n \times m \times N}$ which is a binary control tensor where n, m and N are the number of targets, observers and samples, respectively. Let u_{ijk}, a binary variable, be

an entry of tensor U, where $u_{ijk}=1$ indicates that target i will be inspected by Observer j during sample k.

Let $U_{jk}\in \mathrm{B}^{n\times 1}$ be a binary column vector as Equation 1.

$$U_{jk}=[u_{ijk}],\qquad \text{For}\quad i=1,2,\cdots,n \tag{1}$$

Furthermore, let Q represent the observation quality where L is the number of different sides from which each target must be viewed. Q can be computed using *a priori* knowledge of the motion dynamics of the targets and observers as well as the environmental conditions at least for a short period of time. Each entry of $Q\,(q_{ijkl})$ is a positive number, and it denotes the observation quality of direction l of target i from observer j at sample k (See Section 3.2.1).

Let Q_{jk} be the observation quality matrix for observer j at sample k for all target in all different sides (Equation 2).

$$Q_{jk}=[q_{ijkl}],\qquad \text{For}\quad i=1,2,\cdots,n\quad l=1,2,\cdots,L \tag{2}$$

The CVSM problem can also be expressed by Equation 3 [8].

$$\begin{gathered}
\underset{U}{\text{Maximize}}\,\{\min.[\sum_{k=1}^{N}\sum_{j=1}^{m}\text{diag}(U_{jk})\,Q_{jk}]\} \\
\text{Subject to}: \\
\sum_{i=1}^{n}u_{ijk}\le 1 \\
\text{For}\quad j=1,2,\cdots,m\qquad k=1,2,\cdots,N \\
U\in \mathrm{B}^{n\times m\times N}
\end{gathered} \tag{3}$$

Nourzadeh and McInroy [9] propose an approximate hybrid PTAS algorithm (ILP-Greedy) to solve the CVSM problem. The proposed method can achieve a near-optimal solution by letting each constituent algorithm operate in a domain where they perform better.

3.2.1. Image Quality Assessment

The output of an optical imaging system depends on several physical factors, i.e. lighting, atmospheric attenuation, light diffraction, occlusion, imaging sensor resolution and sensitivity, electronics parts and output devices. In this surveillance application, some physical aspects have a significant influence on the output image. The subsequent subsections develop methods of including the most important physical aspects: light diffraction, occlusion and side observation quality.

3.2.1.1. Light Diffraction

Because of the Fraunhofer (far-field) diffraction phenomenon, even an optical lens with perfect quality has limited performance, and by increasing the object distance, the resolving ability decreases. The image resolving quality for a system with a fixed aperture diameter D and fixed wavelength λ can be expressed by Equation 4, where δ is the distance between the object and the lens.

$$q_{resolve} = \frac{D}{1.22\lambda\delta} \tag{4}$$

3.2.1.2. Occlusion

Since an occluded object can't be inspected by the observer, the resulting image quality for that object should be considered zero. On the other hand, if there is no obstacle between the object and observer the possibility of having perfect image of that object exists (Equation 5).

$$\begin{cases} q_{los} = 0 & \text{occlusion} \\ q_{los} = 1 & \text{no occlusion} \end{cases} \tag{5}$$

3.2.1.3. **Side Observation Quality**

In visual sensor planning, the vast majority of research is mainly concerned with finding the parameters of the vision system to inspect all sides of an object with a minimum number of observations. One simple way to compute this quality is to assign an outward facing unit normal for each face of interest, i.e. let n_{ilk} be the l^{th} outward facing unit normal on object i at sample time k. To determine if a specific side of an object is viewed, let v_{ijk} be the unit vector pointing from object i to observer j at sample time k. Then the observation quality of side l of object i can be computed as in Equation6.

$$q_{view}^{ilkl} = \begin{cases} n_{ilk}^T v_{ijk} & n_{ilk}^T v_{ijk} > 0 \\ 0 & n_{ilk}^T v_{ijk} \le 0 \end{cases} \tag{6}$$

3.2.1.4. **Single Quality Metric**

In order to form a single number reflecting overall observation quality of object i inspected by observer j during sample k along face l, all calculated qualities should be combined. Since overall quality varies from application to application, it can be done by multiplying weighted qualities. This method allows us to control the participation of all constituent parts in a single quality metric. Let q_{ijkl} be the product of all mentioned qualities (Equation 7).

$$q_{ijkl} = q_{resolve}^{ijk} q_{los}^{ijk} q_{view}^{ijkl} \tag{7}$$

For different values of i, j, k and l, q_{ijkl} forms a 4-D observation quality array Q.

3.3. Procedure for Coordinated Patrolling

Consider a surveillance application in which m mobile robots are patrolling an area with some obstacles. While they are detecting some adversaries, they also take N pictures of n pre-defined moving/fixed targets in a 2-D grid-based map of the area within a certain period of time. It is desirable to have decent quality images from different sides of the targets. Now the question is which paths are the best to perform both tasks efficiently. To answer this question, the patrolling and CVSM problems should be merged in a way so they could find some patrolling trajectories for robots on which the patrolling time is minimized and Equation 3 is maximized.

In other words, the TSP problem intends to find the shortest path between key points, while the CVSM tries to maximize the minimum observation qualities of targets. Like many Multi-objective optimization problems, in this design procedure there is a tradeoff between two cost functions.

For the sake of simplicity, suppose that the targets are fixed. In this case, the observation quality of direction l of target i from all points p in the map forms a scalar quality field, and the total effect of this quality field along curve (trajectory) c can be expressed by the line integral in Equation 8. This line integral can be rewritten by Equation 9,

$$\oint_c Q_l(x_i)ds \tag{8}$$

$$\int_{t_1}^{t_2} Q_l(x_R(t), x_i)dt \tag{9}$$

where x_i and x_R denote state vectors of target i and robot j, respectively. In the discrete case, the latter integral will be quality summation over a finite number of points on all the trajectories. $[Qsum_{li}]$ is a matrix representing observation quality for all sides and targets(Equation 10).

$$Qsum_{li} = \sum_{j=1}^{c}\sum_{k=1}^{N} Q_l(x_R^j(k), x_i) \tag{10}$$

Figure 1 depicts some possible solutions for one instance of this mixed problem. Blue circles and red stars represent key patrolling points and targets, respectively. Evidently, the solid-line trajectories are not optimal with respect to the CVSM problem's objective function. For the robots on these trajectories, it is impossible to inspect the sides of targets in arrows directions. For instance, all robots which are moving on path C_1 and C_2 can see only one side of targets $1, 4$ and 3. Therefore, the minimum inspection quality would be zero.

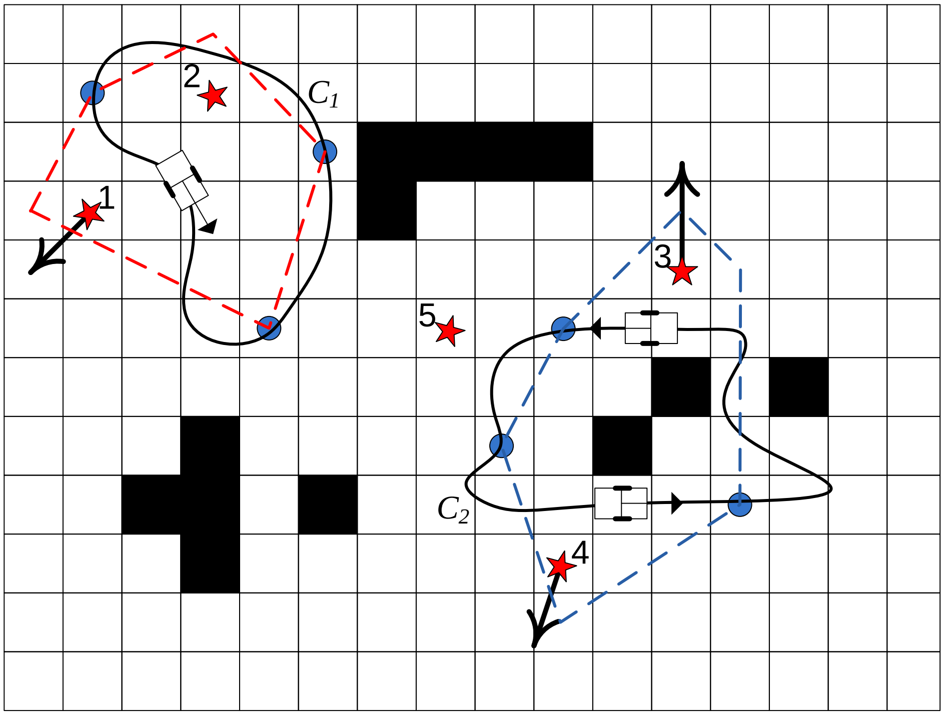

Figure 1. Multi-objective Multi-agent System (Surveillance Application for Mobile Robots)

On the other hand, none of the dotted trajectories is optimal in the sense of sweeping distance. But they make a satisfactory compromise for the Multi-Objective problem. The prime goal of this paper is to devise a PTAS algorithm that finds a near optimal solution for the combined problem.

3.3.1. Proposed Multi-Objective Planning Algorithms

Algorithm 1 states the proposed planning scheme to coordinated design of the Multi-Objective Multi-agent problem. The algorithm begins with solving the patrolling problem for some pre-defined via points. Any algorithm that solves the deterministic patrolling problem can be used to achieve the patrolling trajectories. In this paper, the A^* path finding algorithm is used to find the minimum distances between the patrolling via points. For dynamic maps, one can utilize any un-informed incremental search algorithm such as D^*, etc. After finding distances between via points, the TSP is solved to find the best patrolling trajectories. The resulting patrolling trajectories minimize the revisit time of via points. Any existing approximation scheme can be exploited to achieve the patrolling paths.

In line 2 of the algorithm, matrix Q_{sum} is computed according to Equation 10. This matrix tells how these trajectories contribute in all targets observation qualities from different sides.

Algorithm 1 Coordinated Design of the patrolling and the CVSM problems

Input: Map information, targets states x_i, Patrolling via Points $Ppts$, robots states x_r^j

Output: New patrolling trajectories and CVSM decision tensor U

```
Use a TSP approximation to solve the patrolling problem and find patrolling trajectories
Compute the Qsum matrix
Find the minimum element(s) (J_min) of Qsum
Find the corresponding target and side indices of J_min in Qsum ⟶ (tIdx, sIdx)
Compute the observation quality of side sIdx of target tIdx from free cells in the vicinity of target tIdx.
Among k-largest qualities, choose cell C_ij that has minimum distance from one of the patrolling trajectories
Add C_ij to the patrolling via points set Ppts
Solve the patrolling problem just for updated Trajectory. Update Qsum matrix
If  J_min < tr  then
 |    Goto 3;
End
```

The algorithm continues to find a worst inspection quality among all targets. Then it locally computes observation qualities of that particular side of the selected target from its neighboring free cells. All quality calculations are performed locally, which makes the proposed algorithm fast and efficient.

Among the k-largest quality values, a cell that has the minimum distance from the patrolling trajectories is chosen. Now, it forms a new patrolling trajectory by adding this point to the list of via points of the nearest patrolling trajectory. The algorithm resumes by solving the patrolling problem for the updated trajectory, and updates the $Qsum$ matrix. If this improvement is satisfactory, the multi-agent sensor management algorithm is performed for the obtained trajectories.

Otherwise it keeps changing the trajectories until the minimum observation quality passes threshold tr. The threshold tr is a design parameter used to find an acceptable patrolling/CVSM tradeoff. The difficulty with this parameter is that there is no general rule to tune tr, and the tr value will be different from application to application. Thus a lot of trial and error might be required to find a good tradeoff for the problem at hand.

4. RESULTS AND DISCUSSION

Figure 2 illustrates a planning problem in which three groups of mobile-robots are patrolling an area in three different trajectories. The patrolling via points on patrolling trajectories 1, 2 and 3 are shown by diamond, pentagram and hexagram markers, respectively. While patrolling, they gather visual information from ten different targets (blue arrows) in a 2-D grid-based map. Figure 3 and Figure 4 depict the quality field caused by targets in different sides. In these graphs, observers can take best quality pictures in the red areas. Suppose in this surveillance mission, the minimum required observation quality for all sides of the targets is 0.3 ($tr = 0.3$).

Table 1 shows the computed $Qsum$ matrix on these patrolling paths. In this configuration, since robots on these trajectories cannot inspect at least a side of some targets (side 1 of the target 9 and side 2 of the target 1), the minimum inspection quality would be zero. The side observation qualities less than threshold level are shown in red.

Table 1. Sides Observation Quality of the Targets on the Patrolling Trajectories (*Qsum*)

Sides	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target10
1	6.46	8.56	**0.04**	2.20	8.68	4.35	1.53	**0.14**	**0.00**	17.48
2	**0.00**	**0.19**	8.42	1.74	4.01	**0.10**	7.00	10.42	4.38	5.29

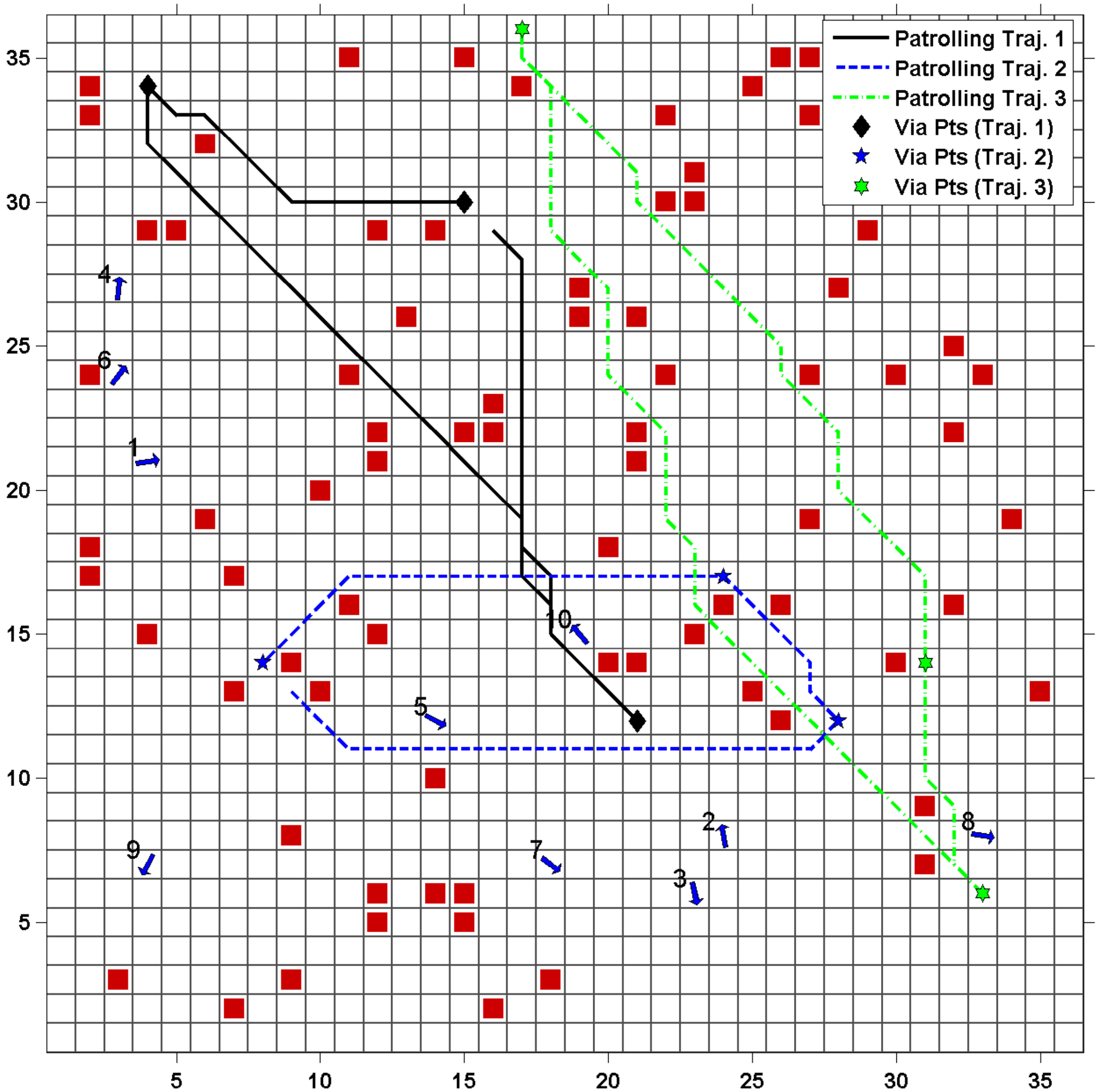

Figure 2. Patrolling Trajectories before Performing Planning

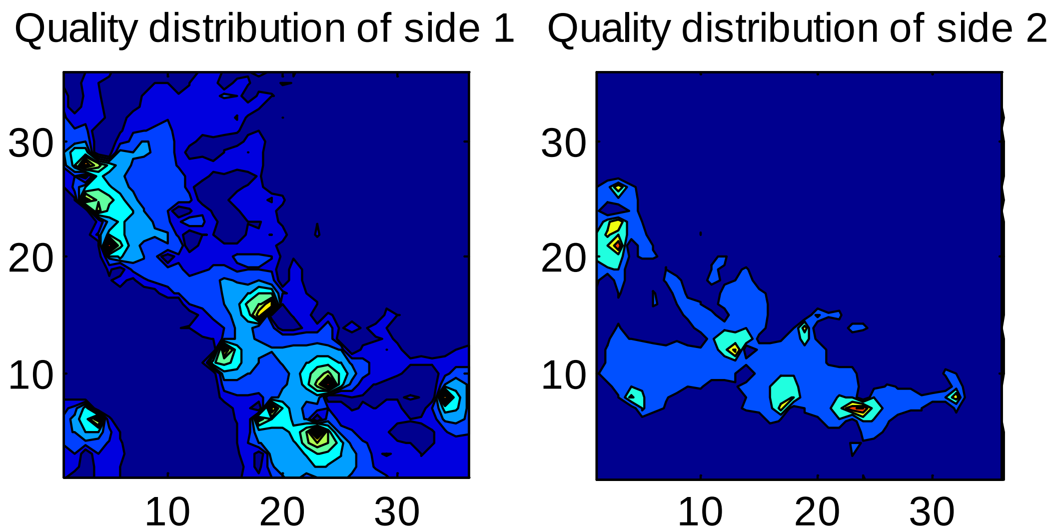

Figure 3. Observation Quality Field for Different Sides of the Targets

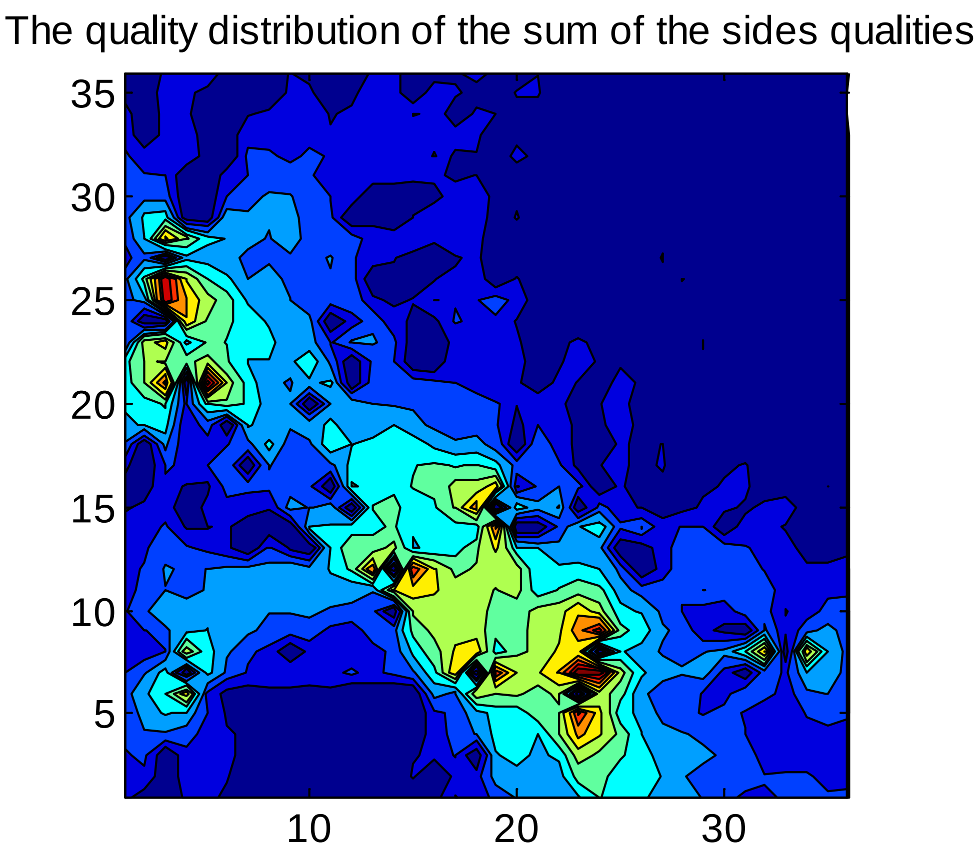

Figure 4. Sum of the Observation Quality Fields of the Targets in Different Sides

Figure 5 illustrates the system configuration after running one step of the proposed Multi-Objecting Muli-agent planning scheme. Note that one via point is added to the patrolling trajectory 1. By looking at Figure 3 , it is obvious that a via point has been added in an area in the

map with high quality level of the side 2. Since this cell has the minimum distance to trajectory 1, it will be added to via points of trajectory 1, and forms a new patrolling trajectory. Table 3 shows the $Qsum$ matrix after performing one iteration of Algorithm 1. Not only is the observation quality of Target 1 improved but also on this new patrolling trajectory side 2 of target 6 is observable with a quality level higher than the threshold $tr = 0.3$.

Figures 6–8, depict the changes made by the proposed algorithm in three successive iterations. Tables 4–6 show the corresponding change to the $Qsum$ matrix.

Table 2. Performance of the Proposed Multi-objective Multi-agent Planning Scheme

Iteration	Revisit time (seconds)			Revisit time percentage increase			$J_{\min}$
	Trajectory 1	Trajectory 2	Trajectory 3	Trajectory 1	Trajectory 2	Trajectory 3	
0	15.546	11.389	36.627	0.000	0.000	0.000	0.0
1	**17.278**	11.389	36.627	**11.143**	0.000	0.000	0.0
2	17.278	**15.010**	36.627	11.143	**31.796**	0.000	0.036
3	17.278	**15.718**	36.627	11.143	**38.005**	0.000	0.138
4	17.278	15.718	**37.042**	11.143	38.005	**1.131**	1.209

Performance of the patrolling and minimum achievable observation quality for all targets are outlined in Table 2. After performing four iterations of Algorithm 1, the revisit time percentage increases for the patrolling trajectories 1, 2 and 3 are 11.143, 38.005 and 1.131 respectively. This increase in revisit time is necessary to improve the visual inspection quality (Jmin). As mentioned before, the threshold level tr can significantly change the performance of both patrolling and CVSM. Like many Multi-objective optimization problems, proposing a general rule to design the threshold level is not straightforward and it varies from application to application.

Table 3. Sides Observation Quality of the Targets after Performing One Step of the Proposed Algorithm ($Qsum$)

Sides	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target10
1	6.16	9.83	**0.04**	5.77	11.80	6.21	1.53	0.14	**0.00**	13.14
2	2.08	**0.19**	9.29	4.98	7.52	1.23	7.78	10.62	5.14	5.38

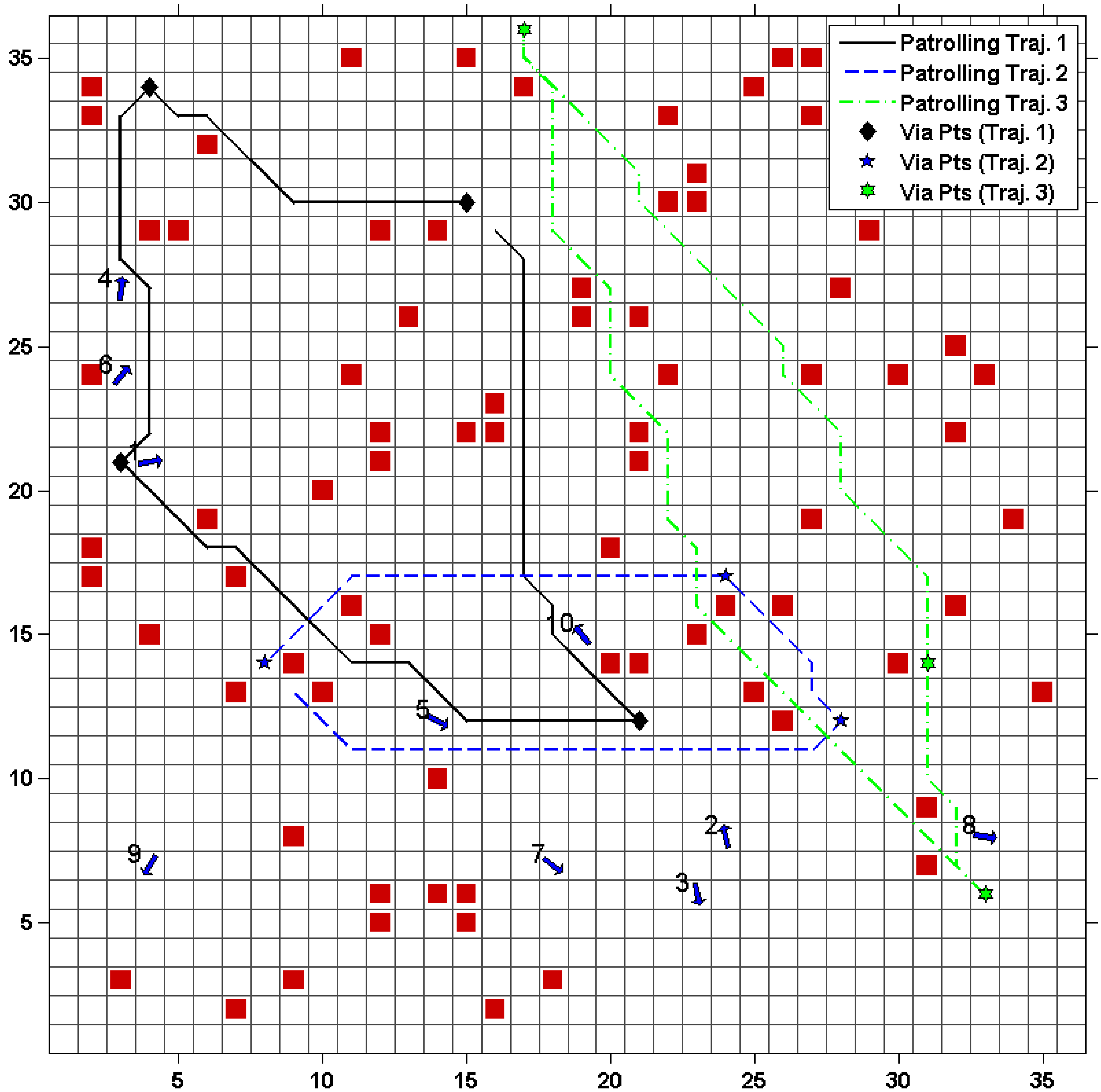

Figure 5. Patrolling Trajectories after Performing One Step of the Proposed Planning

Table 4. Sides Observation Quality of the Targets after Performing Two Steps of the Proposed Algorithm ($Qsum$)

Sides	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target10
1	6.20	11.16	**0.04**	5.77	9.89	6.20	2.18	**0.14**	1.56	13.18
2	2.08	**0.19**	9.83	4.93	7.99	1.23	11.16	11.25	10.27	5.43

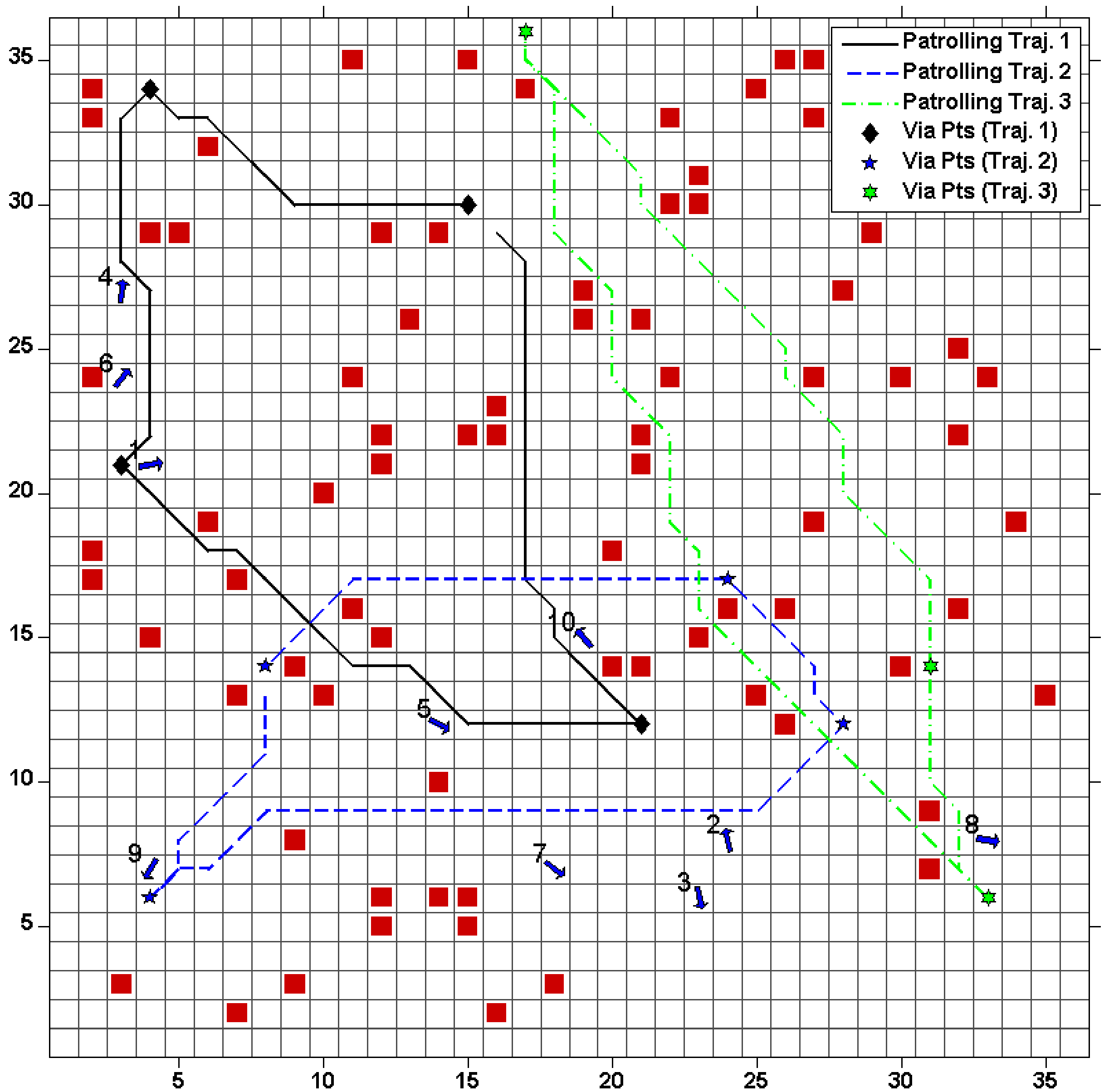

Figure 6. Patrolling Trajectories after Performing Two Steps of the Proposed Planning

Table 5. Sides Observation Quality of the Targets after Performing Three Steps of the Proposed Algorithm ($Qsum$ **)**

Sides	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target10
1	6.10	6.83	3.02	5.77	8.15	6.20	4.93	**0.14**	2.40	13.17
2	2.09	3.90	7.73	4.78	7.22	1.21	6.77	10.46	7.82	4.96

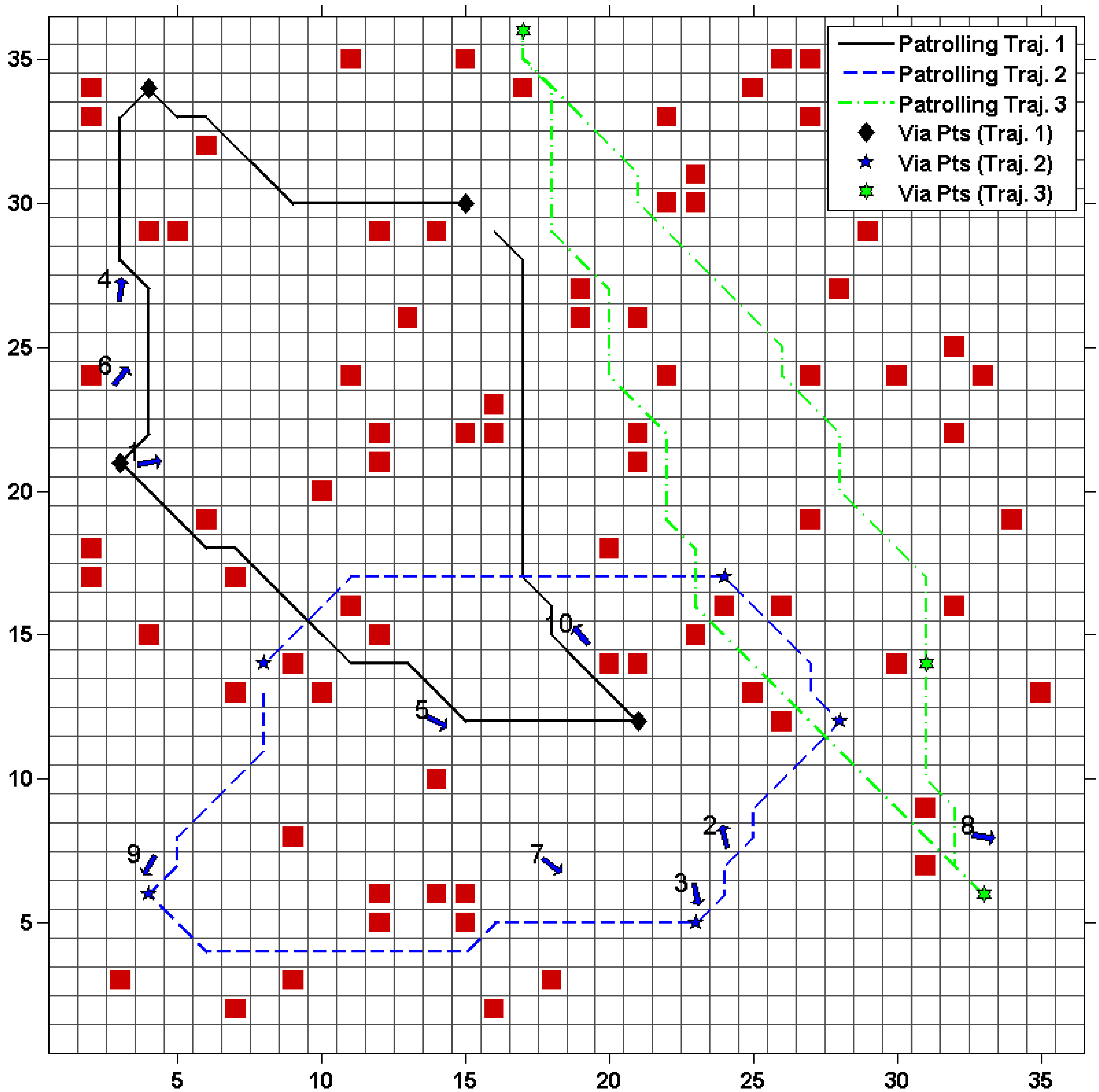

Figure 7. Patrolling Trajectories after Performing Three Steps of the Proposed Planning

Table 6. Sides Observation Quality of the Targets after Performing Four Steps of the Proposed Algorithm ($Qsum$)

Sides	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6	Target 7	Target 8	Target 9	Target10
1	6.03	6.49	3.02	5.77	7.81	6.19	4.72	3.31	2.40	13.04
2	2.09	3.84	7.48	4.75	7.22	**1.21**	6.74	9.86	7.70	4.74

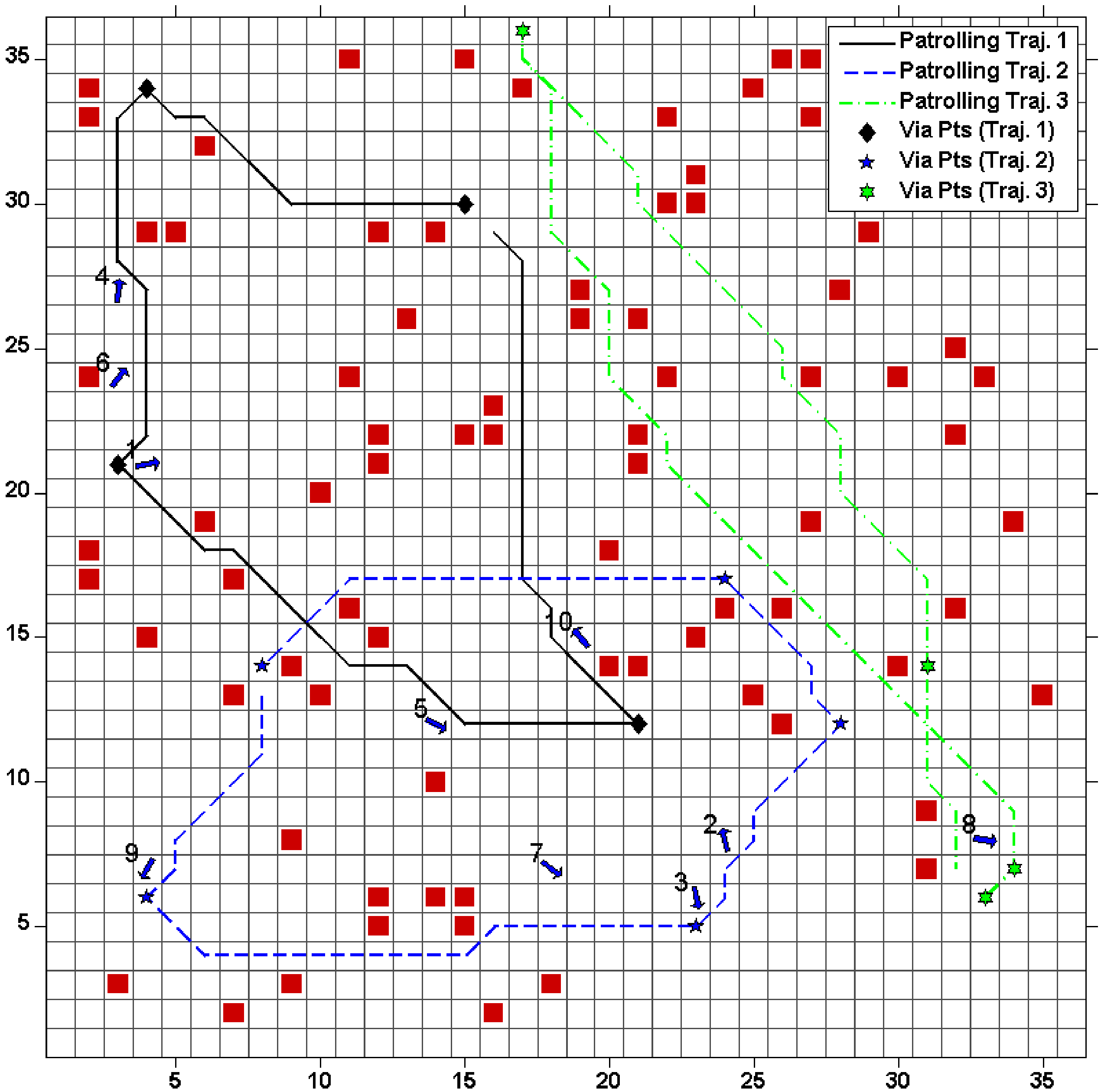

Figure 8. Patrolling Trajectories after Performing Four Steps of the Proposed Planning

The next step after reaching an acceptable level of the observation quality for each target is to solve a CVSM problem for some moving camera (on patrolling trajectories) and some moving/fixed targets given their relative motion. Figure 9 shows the corresponding CVSM problem results based on a method proposed in [9]. Using this hybrid optimization method (ILP-Greedy), a near optimal planning scheme is found in polynomial time. Figure 10 depicts one snapshot of this planning in which six mobile robots are patrolling an area and also gathering some visual information from the targets.

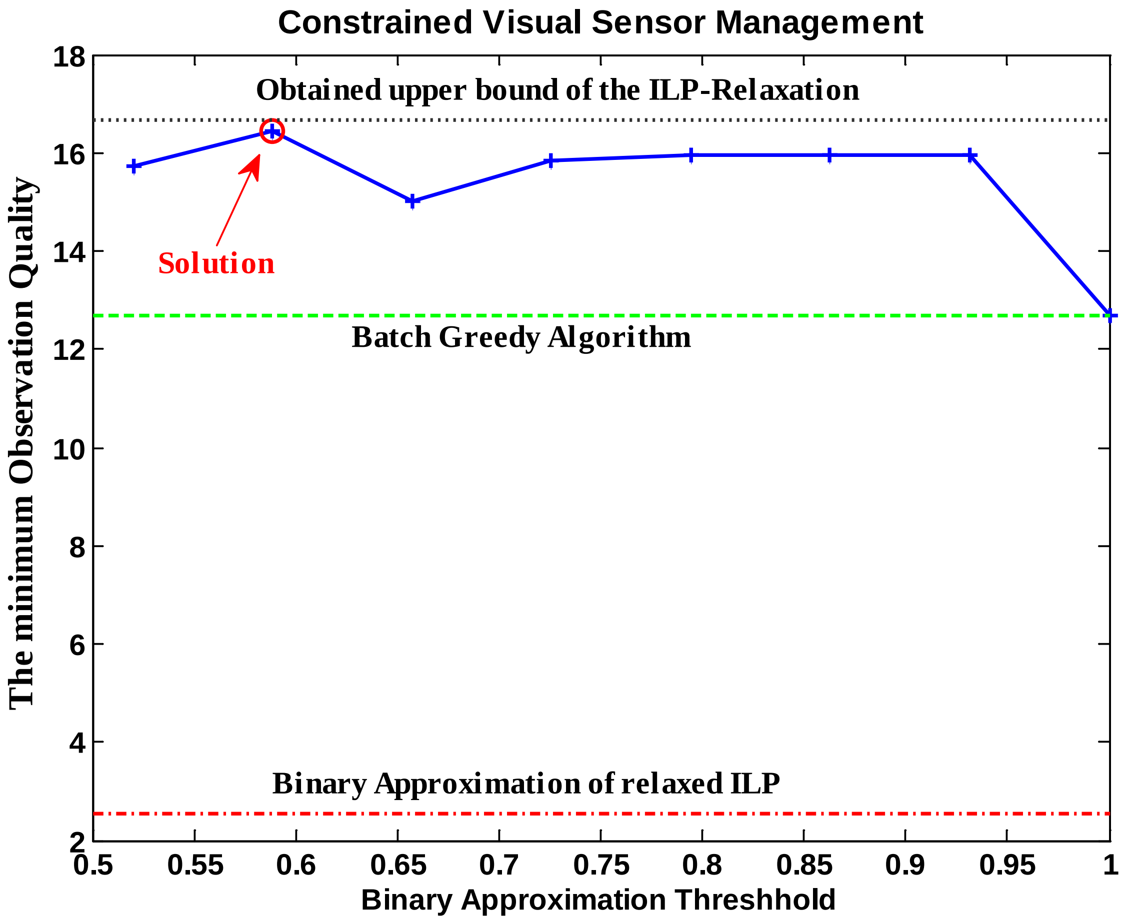

Figure 9. Constrained Visual Sensor Management Result

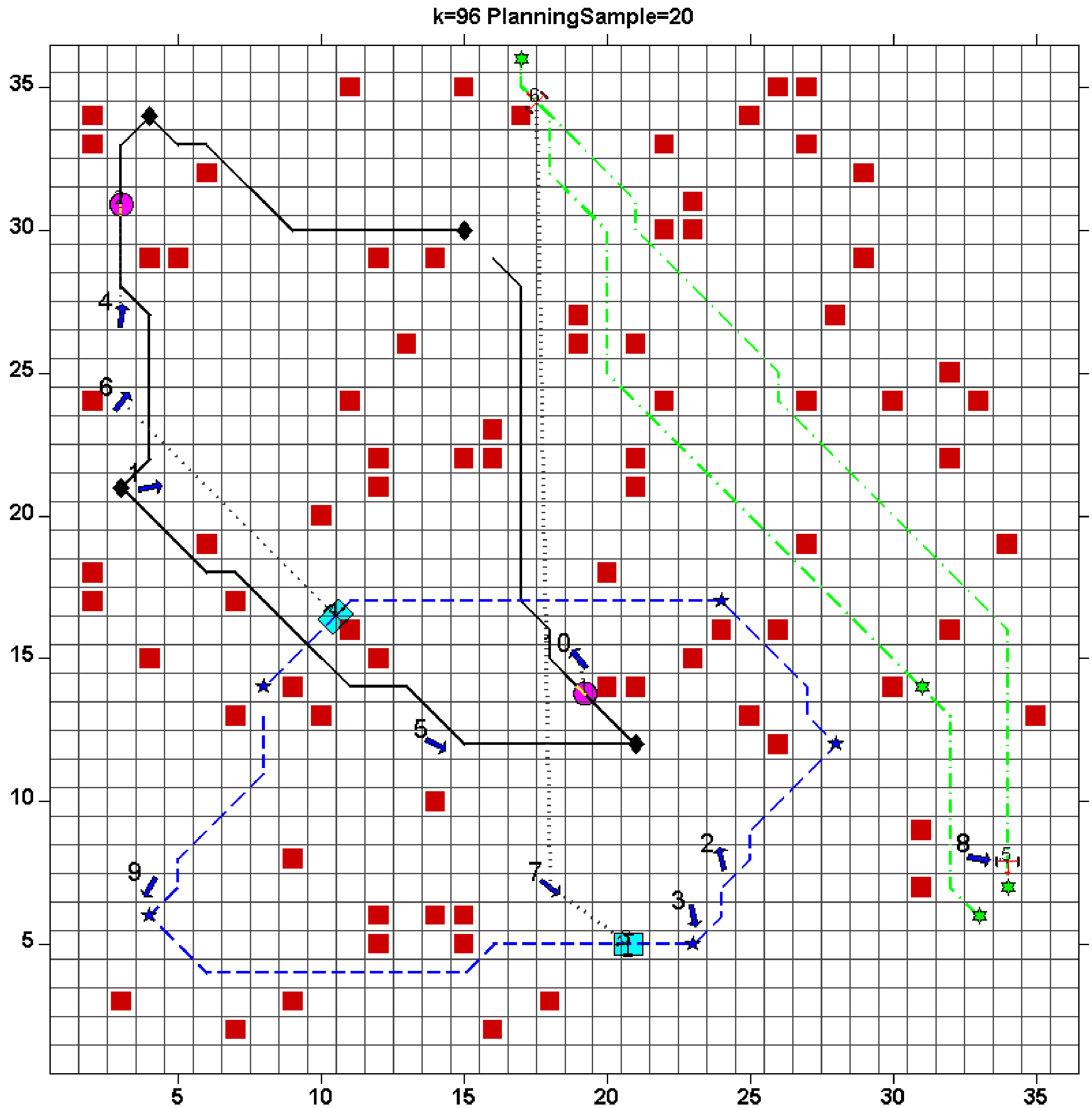

Figure 10. One Snapshot of the Visual Sensor Management Planning

5. CONCLUSIONS AND RECOMMENDATIONS

In this report, a method is developed to determine observation planning for some moving objects and observers (cameras) in which the motion dynamics and the environmental conditions are known. The simulation results are very promising. The length of trajectories are effectively changed by adding one more patrolling via points to each patrolling trajectory. This allows both objectives (patrolling and visual inspection) to be accomplished.

Even with a few number of observers, the proposed scheme designs new patrolling trajectories on which a high level of visual measurement quality is achievable. We recommend the use of this new algorithm as a method to unify control and sensing and thereby enhance situational awareness.

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LIST OF SYMBOLS, ABBREVIATIONS, AND ACRONYMS

CVSM	constrained visual sensor management
ILP	integer linear program
NP	non-polynomial
PTAS	polynomial time approximation scheme
TSP	traveling salesman problem
VSM	visual sensor management